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Article Title: Torque Detection Using EMG Signals for Different Walking Speed of a Person

Torque Detection Using EMG Signals for Different Walking Speed of a Person

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ABSTRACT

This paper analyses the different walking speed of a person for torque detection by using the Electromyography (EMG) signals. EMG measures electrical activity and the muscle response to a nerve stimulation. The reduced ability to move due to variation in tendon structured muscle in lower limb joints of legs affects the overall activity of the human lifecycle. This defect makes it difficult to move causing severe pain resulting in disability. In order to overcome this problem, exoskeleton technology is implemented where Electromyography (EMG) signals are collected from electric impulse generated during the muscle movements. From these electric impulses, the torque present in EMG signals are detected and classified accordingly. The first step consists of pre-processing EMG signals using Infinite Impulse Response (IIR) filter. Secondly features are extracted from pre-processed signals by using Continuous Wavelet Transform (CWT) methods and classified using Convolutional Neural Networks (CNN) classifier. From this classification, the rotational movement of muscles named torque in processed EMG signal is detected. Form detected torque, the normal muscle system and problematic muscle system are differentiated.

Keywords: Electromyography (EMG) signals, Infinite Impulse Response (IIR) filter, Continuous Wavelet Transform (CWT), Convolutional Neural Networks (CNN), and torque.

1 Introduction

In modern days with many technological advancement day-today life of humans is made simpler with reduced human physical activity resulting in unhealthy habits which leads to health issues including neuromuscular abnormalities. Leg weakness and defected leg problems are common among elderly people leading to severe pain and disability affecting the normal human lifecycle. Human muscular problem cannot be detected by using simpler manual detection methodologies. Thus for detecting the human interior problem, exoskeleton technology is invented. Exoskeleton technology is implemented to control or to assist the capability of human activities and in detecting problems in their muscular or skeleton system interiorly. This technology is also implemented in compactible wearable devices with full efficiency [1]. In order to implement the exoskeleton technology, human signals must be collected and computed based on specific learning algorithms. Then from these collected signals, the angle and torques are detected in determining the classification. By detecting these angle and torques various changes in the contraction of muscles are computed and thus makes the classification more reliable [2].

For the implementation of the exoskeleton technology, the EMG signal is detected, from which the gait cycle, torque and the other parameters are determined. For identifying the EMG signal waveform, electrodes are placed on the lower limbs of the human body [3] as the process is for walking speed detection. By computing the EMG signal waveform, variation in the joint torque, knee torque, hip joint torque, muscle contraction are calculated by using electrodes and EMG sensors. These EMG signals are studied in terms of the gait cycle, which is further divided as stance and swing phase [4]. The involvement of gait cycle parameter provides effective control over the exoskeleton technology and computed for calculating the individual grid characteristics and walking speed of the individual [5].

As the EMG signals are obtained by placing large number of electrodes, the EMG signals obtained have heavy electron-skin interface which further causes unwanted distortion, this in turn reduces the quality of the signal. To make this EMG signal classification more accurate, preprocessing technique is deployed. Filtering process involves eliminating the unwanted distortion caused by the motion artefacts, electric noise in the amplifier and other noise sources [6]. One of those techniques used is adaptive filtering method, which is considered even for varying noise environment and to reduce distortion caused due to the human-machine interface. This filter technique adjust the filter weight automatically even for high noise varying circumstances without any fixed frequency range [7]. As drawback, this technique involves higher computation and makes the process more complex.

The classification must be made more accurate to make the results more reliable. Processing the classification using machine learning involves compressing the signal fed into small dimensions and gaining the classification based features [8]. In k-nearest classification technique which is a machine learning technique, the distance is determined and a k-value is set and then by testing the value for multiple time classification is achieved. In support vector machine algorithm, the classification is based on two different classes. In random forest technique, a summarized prediction method is followed [9]. Especially in the random forest with principle component analysis (RFPCA) technique, requires very less time for training data. The error in determining the classification is less when the number of sample signals are increased [10]. Thus machine learning classification technique involves high computations and difficulty in implementing.

Thus to overcome all these difficulties and make the process more effective, torque detection using the deep learning techniques is implemented using CNN classifier. The EMG signal attained from the human leg movement undergo data acquisition and then preprocessed using IIR filter for which the features are extracted using the CWT technique which is further

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classified using CNN. IIR filter makes the process simpler in computation and CWT technique makes the process more reliable even with continuously varying signals therefore, resulting enhanced torque detection with improved accuracy and efficiency.

2 Recent works

Kizyte et al (2023) have developed the ankle joint torque detection system of an EMG signal using the Support Vector regression technique. The angle, torque and the angular velocity are calculated during the data processing. After calculating these signals, they are pre-processed by using the Band pass filtering technique. The feature extraction process is then carried out by the Convolutional neural network (CNN) methodology, where the signals are normalized and the required features are extracted. The SVM method is used in the ankle torque classification which is based on the kinematic features. However, this algorithm is not suitable for large and non-linear datasets.

Analia et al (2019) have demonstrated the joint torque detection using decision tree algorithm for exoskeleton technology. Inertial Moment Unit (IMU) sensor is used for detecting the gait cycle as the input signal to be detected. The gait cycle thus computed is divided as the stance phase and the swing phase. By using the decision tree technique, it is found that the torque required for the right is less compared to the left side, so if the system gets high torque for its right side, then the system is decided to be in its swing phase. This algorithm has the ability to process even any unbalanced set of signals but the decision made is more sensitive for even small changes or variations.

Mokri et al (2022) have analysed the force exerted in the muscle by detecting its EMG signal using various machine learning techniques. Classification and feature selection using support vector machine, random forest and estimation module are analysed. Initially, the obtained EMG signal is pre-processed by sending it through the notch filter, then the signal bias is removed and then signal softening is done by predefined cut-off frequency. The support vector machine is mainly used in the classification which is based on the linear datasets. Random forest technique is used as deep decision making technique. The implementation of classification based on machine learning is simpler but the result is less accurate comparatively.

Márquez-Figueroa et al (2020) have analysed optimized feature extraction and classification techniques in the lower limb motion detection using the EMG signals. The Wilson amplitude (WAMP) technique is used for the optimized feature selection in which whenever the adjacent samples overcome the threshold value, the count are incremented and then noted in order to exhibit optimal selection process with reducing distortion. The optimized classification technique used is the Gaussian Kernel Linear Discriminant Analysis (GK-LDA) where the classification is done based on the Gaussian kernel functions. Even though these techniques are optimized still struggles with complex implementation.

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Tuncer et al (2020) have introduced Ternary pattern and discrete wavelet (TP-DW) based feature extraction in the EMG signal classification methodology. This technique follows channel concatenation, feature extraction and selection, and then classification. The classification process is carried out by the k-nearest neighbour classifier (k-NN). The feature extraction and selection is implemented using polling method, where the input signals are divided into various sets of input samples and then processed. The removal of the entire frequency is replaced by only replacing the unwanted frequency, this increases the system accuracy but the efficiency of the system decrease when less amount of signals are processed.

3 Proposed work

Torque detection using EMG signals is implemented for determining the walking speed of a person and for the diagnosis of neurological and neuromuscular problems. Figure 1 represents the block diagram of the proposed system.

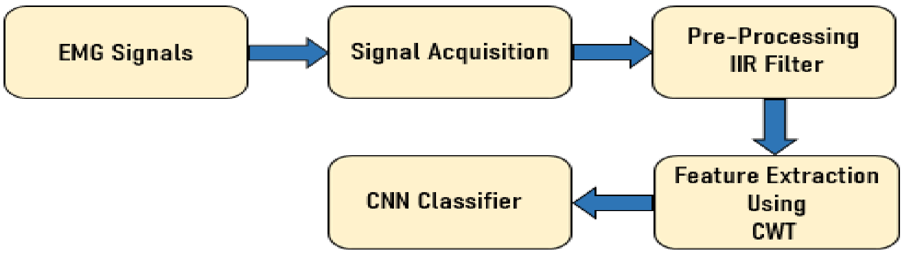

Figure 1: *Block diagram of proposed model*

The electric impulse caused by mechanical output during contraction from leg movement is collected as EMG signal. These signal cannot be directly used for classification process hence data acquisition technique need to be deployed where physical EMG signals are converted to digital data thereby, making it suitable for detection process. Then the EMG signals undergo preprocessing using IIR filter, where all the unwanted artifacts are removed. Features are extracted from the preprocessed signal using CWT technique. Finally classification is done by using CNN technique.

3.1 EMG signal detection

EMG signals is a collection of electrical signals produced during the muscle contraction of the human body representing the neuromuscular activities which are controlled by the nervous system. EMG detection is classified into two kinds namely surface EMG and intramuscular EMG where surface EMG refers to the recording of muscle activity from the surface above the muscle which is recorded using multiple number of electrodes meanwhile intramuscular EMG is recorded using mono-polar electrode needle which are inserted into the human muscles. The EMG signals are obtained from the electric impulses caused by the mechanical action performed due to the leg movements is recorded and processed for accurate classification. EMG signal involving data obtained from five different muscles including Rectus femoris (RF), Biceps femoris (BF), Vastus internus (VI), Semitendinosus (ST), Knee Flexion (KX) are considered for torque detection.

3.2 Gait cycle pattern

Gait cycle represents the cyclic movement during walking or any other movements. One gait cycle starts when one foot heel touches the ground and completes when the same foot heel touches the ground for the next time. Once the EMG signal are detected form body, the gait cycle pattern is produced. Gait cycle consists of two phases namely stance and swing phase where the foot in contact with ground is called as stance phase and the part where foot is not in contact with ground is called swing phase. Stance phase is further divided into five sub-phase namely initial contact, loading response, mid-state, terminal stance and pre-swing similarly swing phase is divided into three sub-phases: initial swing, mid-swing and late swing. Gait cycle is measured using the assessment strategy to determine normal and abnormal gait. These gait cycle are responsible for detecting the torque produced in EMG signal which is further used for pre-processing.

3.3 Signal Acquisition

In data acquisition stage, the physical EMG signal is converted into digital data signals for easy storage, display and analysis thereby, making the further detection process simple with enhanced accuracy. In other words data acquisition refers to the process of converting analog waveforms into digital values for better processing. Data acquisition process consists of three main components namely sensors, signal conditioning and analog-to-digital converters where sensor converts the physical variables into electrical signals then these signals are converted into a specific form which are further converted to digital values by using the converter. Hence, data acquisition process is used in visualising signals for further processing and classification purposes.

3.4 Pre-processing

After the data acquisition process, the signals are pre-processed. This pre-processing technique is used for removing the distortion and unwanted noise in the signal. In the proposed methodology, IIR filter is used for pre-processing technique. As these IIR filters includes feedback technique, the present and the previous data are analysed and thus they have large time limit in impulse responses. Compared to the other filtering methods, IIR filters are easy in implementation and reliable in performance and computation. By this processing the signals are made more cleared and the important features like torque are highlighted. The relationship between the input and output of IIF filter is given by,

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$$y(n) = -\sum_{k=1}^{N} a(k)y\,(n-k) + \sum_{k=0}^{M} b\,(k)x\,(n-k) \tag{1}$$

Where, the output sample is obtained from the previous M inputs and N outputs with the current input samples. Since IIR is a linear system the input and output is associated by the recursive relationship. Recursive relationship requires N+M+1 multiplications and N+M additions.

$$y(n) = \sum_{k=0}^{\infty} n(k)x\,(n-k) \tag{2}$$

The above equation is re-arranged as,

$$\sum_{k=0}^{N} a(k)y\,(n-k) = \sum_{k=0}^{M} b\,(k)\,x\,9n-k) \tag{3}$$

If a (0) = 1, the above equation is written as,

$$\sum_{k=1}^{N} a\,(k)\,[z^{-k}y\,(n)] = \sum_{k=0}^{M} b(k)\,[z^{-k}\,x\,(n)] \tag{4}$$

Where z^{-1} is considered as unit delay operator hence,

$$z^{-k}\,x(n) = x(n-k) \tag{5}$$

Hence, transfer function in terms of z is expressed as,

$$H(z) = \frac{y(n)}{x(n)} = \frac{\sum_{k=0}^{M} b(k)z^{-k}}{\sum_{k=0}^{N} a(k)z^{-k}} \tag{6}$$

The ration of two polynomials is given by,

$$= \frac{b(0)+b(1)+\cdots+b(M)z^{-M}}{1+a(1)z^{-1}+a(2)z^{-2}+\cdots a(N)z^{-N}} \tag{7}$$

3.5 Feature extraction

The features are extracted from the pre-processed EMG signal by using the CWT technique. CWT technique is used in order to extract feature even form large datasets in more accurate manner. The feature extraction are time based that is easily converted in frequency domain. Converting signals from the time domain to the frequency domain makes the feature extraction reliable for equalization, data analysis and pattern detection process with more accuracy in frequency domain. CWT execution is based on the band-pass filter which enables CWT to evaluate and identify localised anomaly in time series analysis allocated during equal time intervals. This makes the process of detecting the torque present in the EMG signal more effective and accurate. CWT of signal f (t) is at scale 'a' and time 'b' is given by,

$$W\,(a,b) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\psi * \left(\frac{t-b}{a}\right)\,dt \tag{8}$$

Where $\psi\,(t)$ is CWT, * is the complex conjugate and 'a' and 'b' are the translation and dilation parameters. Minimum values of 'a' produces high frequency whereas maximum value of 'a' produces low frequency functions.

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3.6 Classification based on torque

The feature extracted EMG signal is further classified using the CNN classifier. CNN consists of 12 layers namely input layer, convolutional layer, pooling layer, fully-connected layer and output layer along with normalization, activation and pooling function where the dropout later is deployed for the regularization effect. Pooling layer deployed is used to extract the map features from the given input in order to minimise the overfitting errors and in the convolutional layers the output from pooling layer is converted into nonlinear activation function which is expressed using the below equation,

$$h_i^{l,k} = f\left(b_i^{l,k} + \sum_{n=1}^{N} W_{n,i}^{l,k} * x_{i+n-1}^{l-1,k}\right) \quad (9)$$

Similarly, Average pooling or Maximum pooling output expression is given by,

$$o_i^{l,k} = f\left(\propto_i^{l,k} pool\left(x_i^{l-1,k}\right) + b_i^{l,k}\right) \quad (10)$$

Where $o_i^{l,k}$ is the output of the *l* layer of the i^{th} neuron, *f ()* is the activation function, $b_i^{l,k}$ is the offset neuron, $x_i^{l-1,k}$ is the output of the *l-1* layer and $x_i^{l-1,k}$ is the output of the neuron in the *l-1* layer where *pool ()* is pooling function.

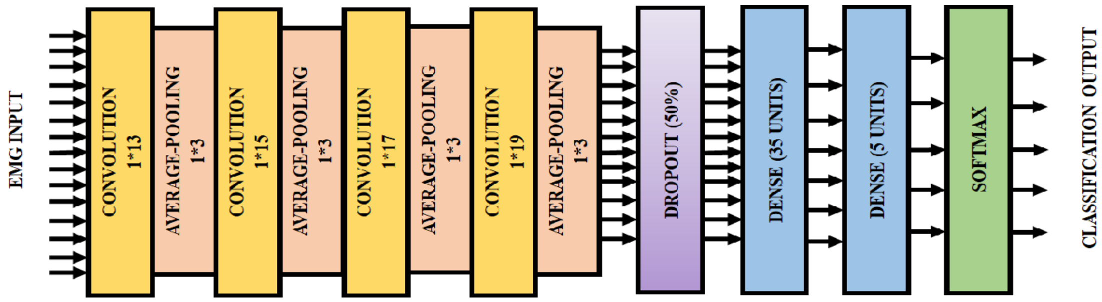

Figure 2: *Architecture of CNN model*

Figure 2 represents represent the architecture of the proposed CNN model. The output from pooling layer and convolutional layer is transferred into the fully-connected convolutional layer where softmax layer is used to make logistic regression classification. In order to reduce joint adaptability among neuron nodes dropout layer is deployed which temporarily disconnects the neurons from the network thereby, eliminating overfitting issues and enhancing the performance ability of the network. The output of the fully-connected layer is given by the equation,

$$o_i^{l,k} = f\left(w_i^{l,k} x_i^{l-1,k} + b_i^{l,k}\right) \quad (11)$$

Each input dataset is divided into test dataset, trained datasets and validation dataset. The validation dataset is deployed to track the training process in order to prevent over-fitting and under-fitting. Finally parameter tuning is performed to attain better optimization. The training dataset are used for training CNN classifier in order to classify torque for the detection of

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healthy limbs or non-healthy limbs. The test dataset are fed into the classifier for checking accuracy of CNN classifier for detecting healthy and unhealthy lower limbs in people. Therefore, the torques Classification is carried out based on the CNN algorithm results in more accurate result with reliable computation.

4 Results and discussion

This paper proposes the detection of torque using EMG signals to determine the walking speed of the person. The EMG signals undergo data acquisition for the conversion of signals into digital data which are further pre-processed for artifacts removal and then feature extracted finally classified using CNN to achieve enhanced torque detection.EMG signal of data obtained from five different muscles including Rectus femoris (RF), Biceps femoris (BF), Vastus internus (VI), Semitendinosus (ST), Knee Flexion (KX) are considered for torque detection and classification.

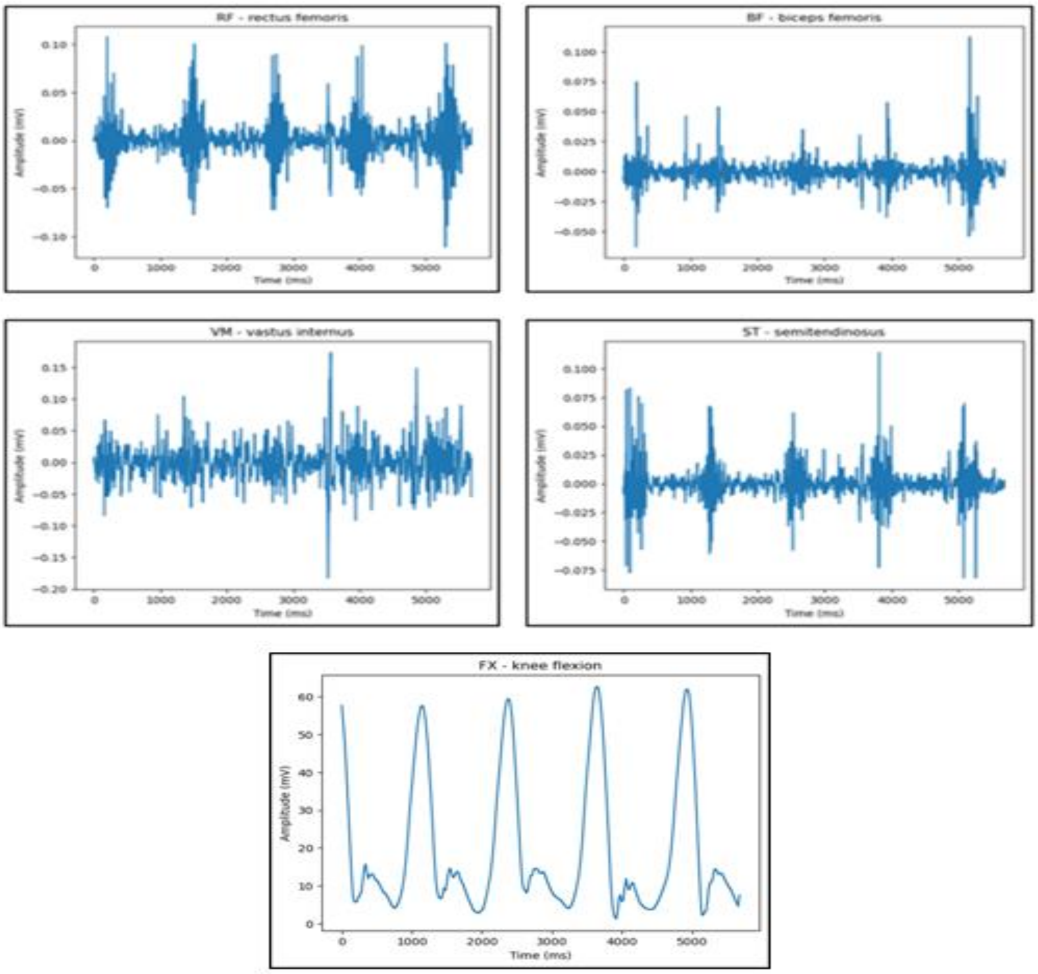

Figure 3: *Input EMG signals*

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Figure 3 represents the input EMG signal fed for the classification process. These are the EMG signals of RF, BF, VI, ST, KX muscular parts present in the lower limb. These signals are unprocessed, which are obtained by placing electrodes on the lower limb.

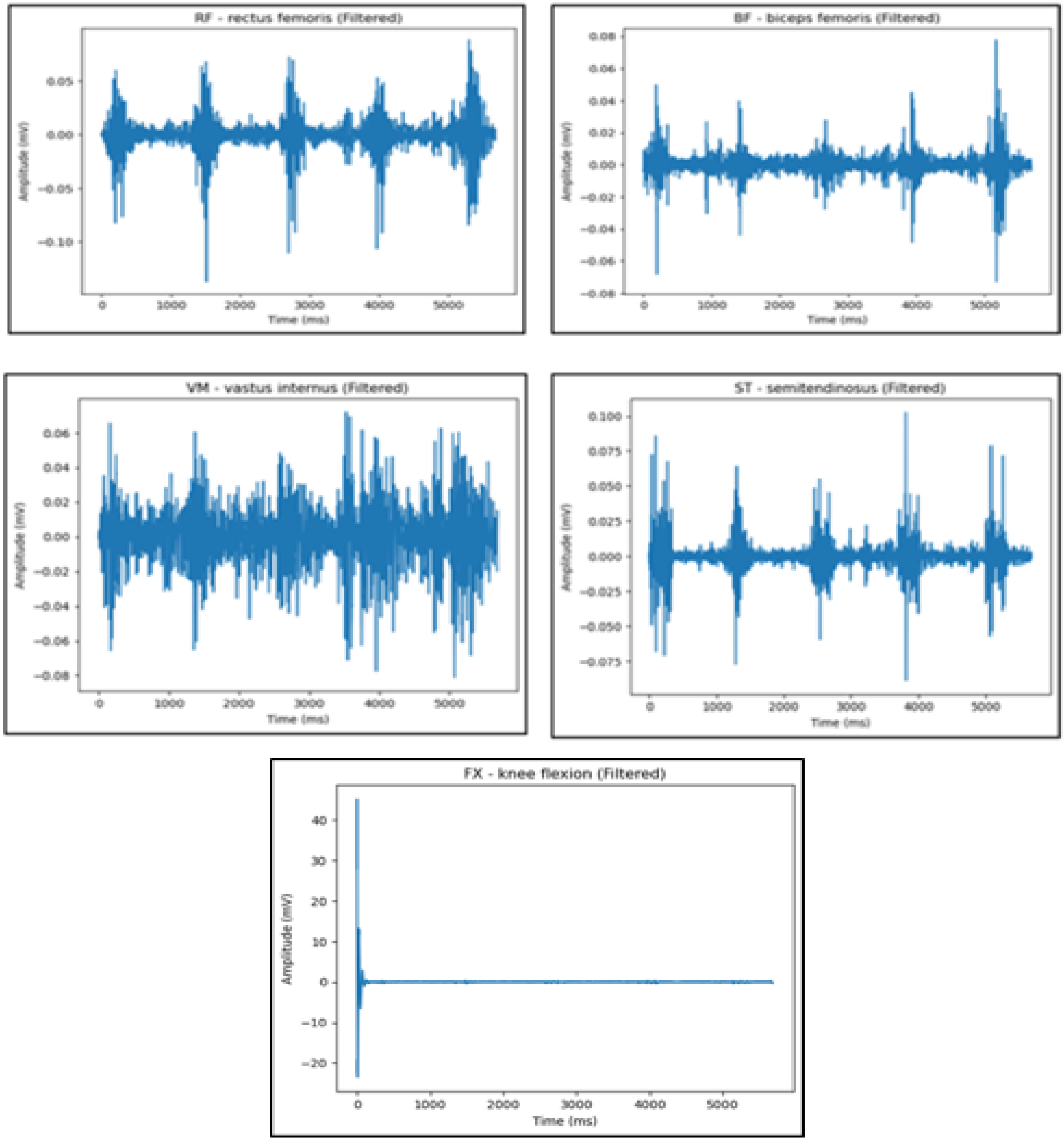

Figure 4: *Filtered EMG signals using IIR filter*

Figure 4 represents the filtered EMG signal of RF, BF, VI, ST, FX muscular parts present in lower limb. These signals are filtered by using IIR filters where unwanted distortion are removed for reliable classification process.

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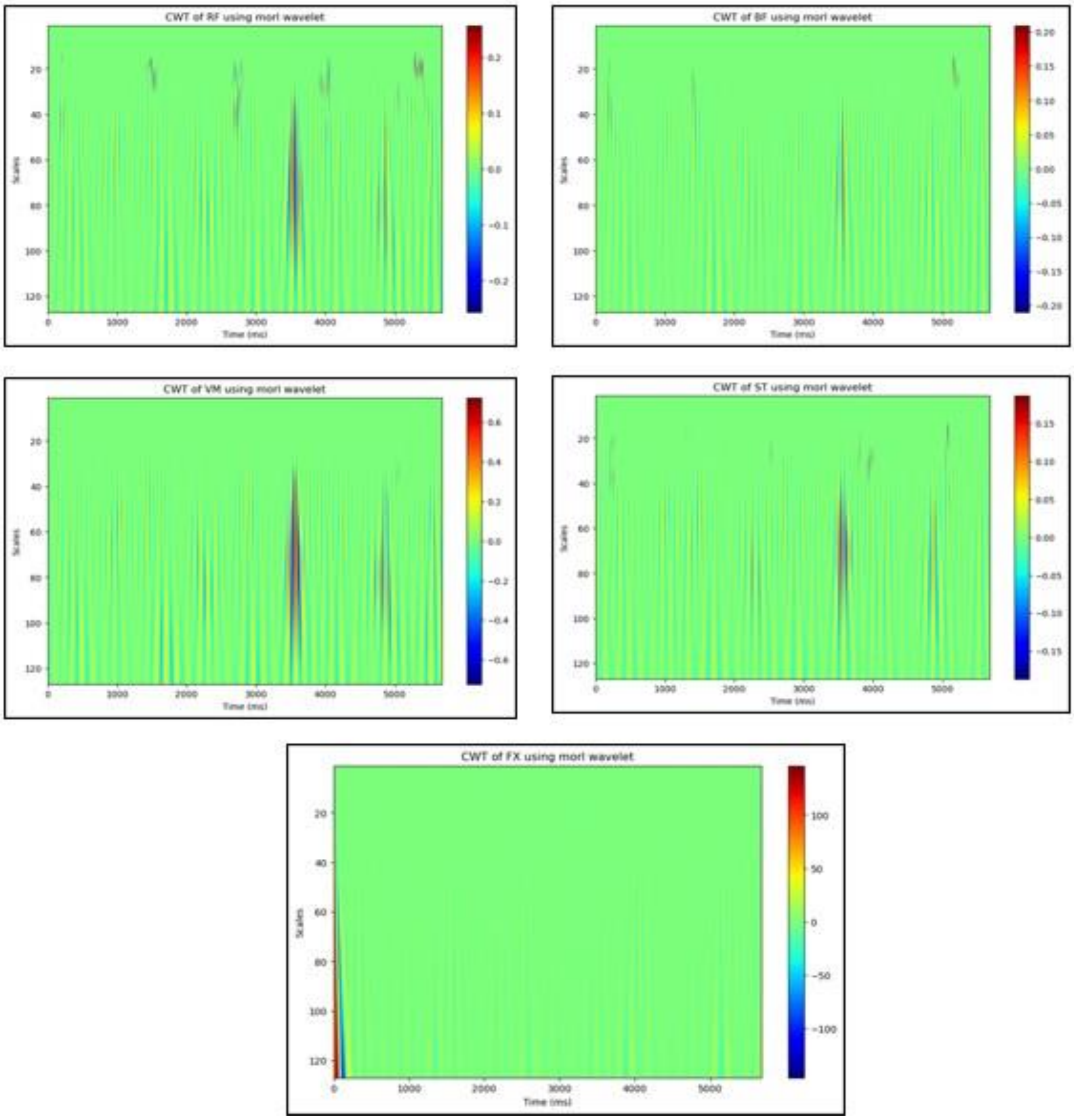

Figure 5: *Feature extraction using CWT Technique*

Figure 5 represents the feature extracted from the EMG signals of the RF, BF, VI, ST, KX muscular parts present in the lower limb. This feature extraction process is carried out by the CWT technique, by converting them into frequency domain set. This feature extraction makes the classification process more accurate.

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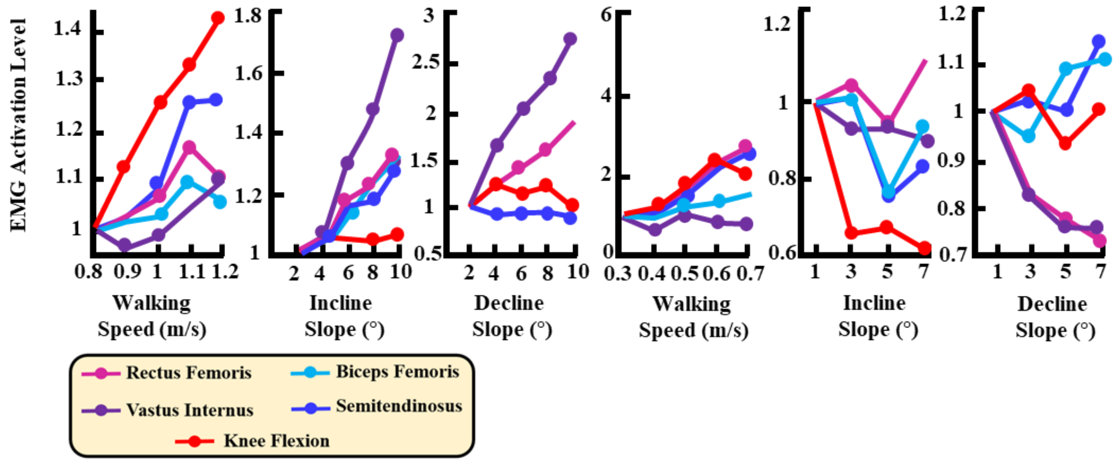

Figure 6: *Torque level classification of normal and defected leg movement*

Figure 6 represents the torque level classification of EMG signals measured. First three graph shows torque level classification for person with normal and healthy lower limb activities. Next three graphs represents the torque level classification for person with defected or unhealthy lower limb activities. The three different graphs represent the torques detected during the normal walking speed, walking in the inclined slop and in the declined slope. As observed, the vastus internus is increasing in the normal graph but it is decreasing in unhealthy or defected graph .Likewise all the other metrics are observed for effective classification.
A comparison chart for the accuracy of various classifiers are depicted in a bar chart.

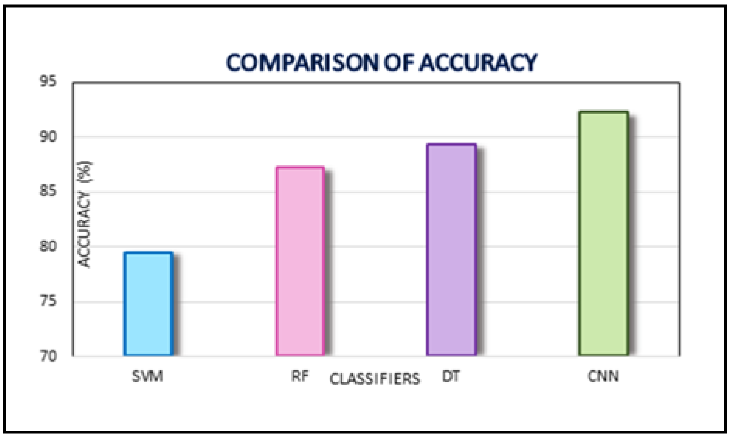

Figure 7: *Comparison chart of accuracy*

Figure 7 represents the comparison chart of accuracy of four different types of classifiers in detecting the torque from EMG signal. By this comparison, it is noted that the deep learning classifier Convolutional Neural Network (CNN) has higher accuracy compared to that of the

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other machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF) and Decision Tree (DT) with 92.3% accuracy in detecting the torque from the fed EMG input signal.

5 Conclusion

Torque detection from EMG signals for different walking speed of a person was developed and analysed using the CNN classifier. The torque obtained from the electric impulses of the leg movement is detected and examined using python software. The EMG signals is converted into digital signals by the data acquisition method. The signals are pre-processed using IIR filters and features are extracted using CWT technique for better classification with enhanced accuracy and efficiency. Therefore, torque detection using EMG signals for different walking speed of a person is detected, examined and classified effectively.

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